Female performance and participation in computer science - a national picture

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Abstract

The change in the English computing curriculum and the shift towards computer science (CS) has been closely observed by other countries. Female participation remains a concern in most jurisdictions, but female attainment in CS is relatively unstudied. Using the English national pupil database, we analysed all exam results (n=5,370,064) for students taking secondary school exams in 2016, focusing on those students taking GCSE CS (n=60,736) contrasting this against ICT (n=67,359).

Combining gender with ethnicity and the IDACI poverty indicator, we find that females from the poorest areas were more likely to take CS than those from the richest areas and CS was more popular amongst ethnic minority females than white females. ICT was far more equitable for females and poorer students than CS.

CS females typically got better grades than their male peers. However, when controlling for average attainment in other subjects, males got 0.31 of a grade higher. Female relative underperformance in CS was most acute amongst large female cohorts and with girls studying in mixed-gender schools. Girls did significantly better than boys in English when controlling for CS scores, supporting theories around female relative strengths lying outside STEM subjects.

The move to introduce CS into the English curriculum and the removal of the ICT qualifications look to be having a negative impact on female participation and attainment in computing. Using the theory of self-efficacy we argue that the shift towards CS might decrease the number of girls choosing further computing qualifications or pursuing computing as a career. Computing curriculum designers and teachers need to carefully consider the inclusive nature of their computing courses.

1 Background

1.1 The English education system

England has a complex education and qualification system for schools (Department for Education 2012). It has a national curriculum (Department for Education 2013b), establishing by law what is taught to five to 16 year olds in those schools controlled by local authorities. The national curriculum is determined by the education minister and approved by parliament. For the significant number of children in schools funded directly by central government, individual head teachers have considerable autonomy over their curriculum, although most choose to follow the national curriculum.

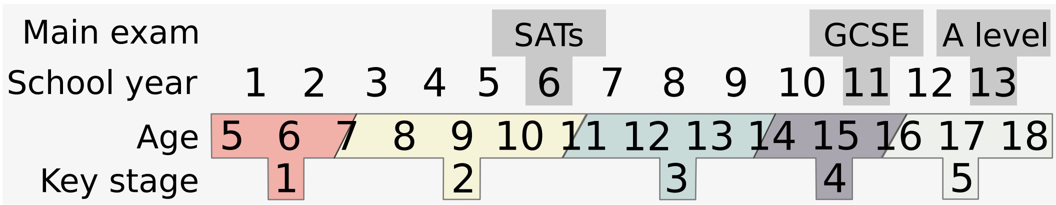

Figure 1: Outline of the English school system by age, key stage and major exam

Schools years are grouped into 5 key stages (KS) covering the ages 5 to 18. Major examinations take place at the end of KS2, in year 6; at the end of KS4, in year 11; and at the end of KS5 in year 13.

In year 6 students aged 10 and 11 sit Statutory Assessment Tests, also known as SATs, in English and mathematics. Between the ages of 14 and 16, almost all students study for the General Certificate in Secondary Education (GCSE) qualifications. These are available in a wide range of academic and creative subjects: most students will take qualifications in maths, English and science, plus further qualifications of their, or their school's choice. Between age 16 and 18, many students go on to study for General Certificate of Education Advanced Level (GCE A level, or just A level) qualifications. Again, these are available in a range of academic and creative subjects, with most students studying for three qualifications at this level. Entry to university courses is typically based on performance at A level, entry to A level courses is similarly based on performance at GCSE. The broad scope of these qualifications is determined by the Department for Education (DfE) (2016b, 2017) and the qualification regulator (Office of Qualifications and Examinations Regulation 2017), but the syllabus and assessment arrangements in any subject are developed by several competing exam boards, subject to accreditation by the regulator.

1.2 The introduction of computing

In 2014 the English national curriculum was changed, replacing Information Communication Technology (ICT) with a new subject, computing. Computing places more emphasis on computer science and programming, although reference is still made to computer applications, a core component of the old ICT specification (Brown et al.

2014), and to pupils' safe and responsible use of technology. The introduction of computing was accompanied by the creation of a new GCSE in computer science (CS). GCSE CS (e.g. Oxford Cambridge and RSA 2012) covers areas such as programming, ethics, hardware, software, data representation, databases and networking. Topics such as programming would be directly tested through written exams and practical programming sessions. In September 2017 the GCSE in ICT was discontinued (Department for Education 2015a). GCSE ICT (e.g. Assessment and Qualifications Alliance 2014) covered areas such as the systems life cycle, spreadsheets, databases, graphics, desktop publishing, collaborative working and the impact of technology. This shift in the qualification landscape leaves students who are interested in a computing GCSE no option other than to study computer science.

The change in curriculum has been closely observed by other countries looking to learn lessons from the implementation (e.g. Caspersen et al. 2018; Moller and Crick 2018; Informatics Europe 2014; Taylor and Downey 2018). There was early speculation that the introduction of computer science would create an elitist and selective subject (Rudd 2013). More recently there have been concerns that the move away from the more 'creative' ICT subject and a focus on technical computing through computer science and programming, "could generate another level of the digital gender divide, even among those who are digitally skilled" (Wong and Kemp 2018, 302). This paper looks to outline the impact of curriculum change in England, towards computer science, on female participation and attainment; it will do this by looking at GCSE examination entries and results.

Initial analyses of the new GCSE show that it is failing to attract girls in similar numbers to the legacy ICT qualification (Kemp, Wong, and Berry 2016; Kemp, Berry, and Wong 2018; Royal Society 2017). Student numbers taking the new computer science GCSE have increased each year since its introduction, but at the same time girls as a percentage of all computing students have decreased (2013: ~40%; 2016: ~32% Kemp 2017; 2017: 30% Kemp, Berry, and Wong 2018). This decrease can be attributed to the male dominated GCSE CS making up a larger proportion of all GCSE computing qualifications, and the more equitable GCSE ICT decreasing in representation. In 2017, for computer science, around one in five (c. 20%) GCSE students and one in ten (c. 10%) A level students were girls, compared to two in five (c. 40%) for ICT (Joint Council for Qualifications 2017b, 2017a). Black and working class students are also underrepresented in computer science qualifications compared to ICT, and to the national cohort (Kemp, Berry, and Wong 2018). When girls do sit ICT and computer science GCSE, they outperform boys in raw grade scores (Kemp, Wong, and Berry 2016; Kemp, Berry, and Wong 2018).

The Royal Society's (2017) report on computing found the main reason given by girls for not choosing to study computer science was "Not interested in subject", with 55% of girls giving this response, compared to 38% of boys. The reasons for the small numbers of girls sitting the course and for this response are likely to be complex, involving a mix of sociological and psychological factors. We cover some of these below.

There are psychological differences between male and female populations (Schmitt et al. 2017) with much debate around how these differences emerge. This debate is outside the scope of this paper; instead, we outline the psychological factors that are correlated to participation and attainment in computer science. Existing studies suggest that computer science is more appealing to the average male (e.g. Royal Society 2017). Some literature shows that boys are more likely to command top grades at degree level (Wagner 2016), and other literature indicates that girls outperform boys at school level computer science (Kemp, Wong, and Berry 2016).

The qualification looked at in this paper is the GCSE, an examination generally taken at the age of 16 in English secondary schools. GCSE CS is not solely about computer programming, but as programming makes up a large proportion of the qualification (e.g. Oxford Cambridge and RSA 2012)[1], for the purpose of this article, literature on programming and computer science will be studied. It should be noted that within the English school system, computing as a subject incorporates elements of computer science, information technology and digital literacy (Kemp 2014). Where the word *computing* is used by us in this paper, it should be taken to mean the subject as a whole, encompassing all three of these elements. However, it should be noted that several sources covered use the words computing and computer science interchangeably. This paper compares the students taking CS and ICT GCSEs looking at how gender is related to participation and attainment in these qualifications. This allows us to argue more widely about how a curriculum shift towards computer science might affect female uptake of any computing qualification.

1.3 Female participation in computing

In most western countries, girls generally engage with technology just as much as boys and there are few reported gender differences in terms of internet or social media usage (Office of Communications 2015). However, in schools, there is a low female uptake of computer science qualifications (Royal Society 2017; Kemp, Berry, and Wong 2018), a pattern seen at degree level in the UK and other developed countries (Wagner 2016). More broadly, there are concerns that girls lack educational and career aspirations in computer science, which is often considered to be gendered as a male domain (Wong and Kemp 2018). These gendered discourses are often reinforced by parents, teachers and the media (Cohoon and Aspray 2006; Sefton-Green and Brown 2014; Vekiri 2013). The disparity in representation is not universal, with cultural factors appearing to create environments for high levels of female CS participation in some non-western countries, including at degree level (Vitores and Gil-Juárez 2016).

ICT focuses on the knowledge and application of 'office productivity' and other end-user software, which is likely to have wider appeal as generic and transferable digital skills that are valued in many workplaces. ICT is often regarded by students as

[1]The assessed non exam based programming component of the GCSE was dropped in 2017, so it is now feasible that a student could sit an exam without writing any code on a computer. `https://www.gov.uk/government/consultations/consultation-assessment-arrangements-for-gcse-computer-science`

a generic skill-set, rather than as a specific career pathway, which remains somewhat reserved for the tech savvy, typically male, candidates (Lasen 2010).

Computer scientists, and those who are tech savvy, are often portrayed in the media as male geeks or nerds, who embody specific characteristics, such as being highly logical and clever, but also stubborn and socially inept (e.g., Varma 2010). These images help to reinforce the idea of computer science as a predominantly male domain and maintain rather than challenge the dominant gender paradigm and roles (Butler 2011).

From an early age, girls and boys are likely to be socialised with different expectations and interests (Margolis and Fisher 2003; Varma 2010). For example, boys are typically expected to be more technical, risky and adventurous than girls, who are socialised into roles that tend to make safer choices, and be more creative and caring (Francis and Skelton 2005). The characteristics of computer science seem to align more with the attributes expected of boys, as programming is generally considered as a technical activity. Stereotypical ideas around gender and computer science may also be facilitated through gender-specific toys and leisure activities, such that computer games are typically targeted at boys whereas more passive and caring toys (e.g., dolls) are typically marketed to girls (Scantlebury and Baker 2013).

Although studies have suggested that there is now better gender equality in terms of digital access and technology interest (Vekiri 2013), others have found gender differences in terms of frequency and types of computer use, as well as self-efficacy and aspirations in digital technology (e.g., Margolis and Fisher 2003; Varma 2010; Wong 2016a). Boys appear to use computers more for gaming, whereas girls seem to use computers and the internet more specifically for social media (Drabowicz 2014). Stoilescu and Egodawatte (2010) also found that girls are generally less interested in coding, even amongst undergraduate computer science students. Furthermore, girls continue to self-report lower confidence in their CS abilities than boys as the subject computer science is generally considered by young people, particularly girls, as challenging and tedious (Lasen 2010; Vekiri 2013).

The Royal Society (2017) noted that girls studying in single-sex schools were more likely to sit GCSE CS than those attending mixed-gender providers; additionally, female GCSE CS cohort sizes in single-sex schools are greater than those in mixed-gender institutions (Kemp, Berry, and Wong 2018), although it should be acknowledged that girls' schools are less likely to offer GCSE CS than mixed providers (ibid.). It has been shown that all-female computer science classes at high school may result in better attitudes towards the subject, when compared to mixed classes (Crombie, Abarbanel, and Trinneer 2002). This contrasts with other findings that all-girl CS engagement events were less likely to keep girls interested in CS than mixed events (Quigley 2017). Whilst poorer students are less likely to study GCSE CS than ICT, when combining gender and ethnicity with poverty indicators, 2015 data shows that among female students, those from working class backgrounds made up a larger proportion of the female cohort than working class boys make up of the male cohort. This pattern is even more apparent for working class Asian[2] and Chinese girls (Kemp, Wong, and Berry 2016).

High attainment in mathematics is associated with increased uptake of GCSE CS (Royal Society 2017; Kemp, Berry, and Wong 2018), with some schools using mathematical attainment as a filter for entry to a computer science GCSE (Kemp, Wong, and Berry 2016). However, this filter is not equally applicable to males and females, as females outperform males at mathematics (Bramley, Rodeiro, and Vitello 2015), yet are underrepresented in CS. How mathematical achievement differs between male and female populations is currently unclear and explored in this paper.

Boys make up the majority of autistic individuals (e.g. Brugha et al. 2009; Constantino and Todd 2003), and autistic traits are correlated to an increased interest in mathematics, science and computer science (Baron-Cohen et al. 2001). Supporting this, autistic traits have been shown to correlate with an interest in hacking (Schell and Melnychuk 2011). Baron-Cohen (2009), as part of the *empathizing-systemizing* theory, claims that autism is an example of the *extreme male brain*, with autistic traits existing on a continuum where boys are more likely to demonstrate them. It follows that *if* autistic traits are linked to an increased interest in computer science, *and* boys are more likely to have autistic traits than girls, *then* boys will on average be more likely to be interested in CS than girls. However, this finding should be taken with caution, as biology is not the only factor that impacts a person's interests, see above, and Gould and Ashton-Smith (2011) suggests that the true number of autistic girls is underreported.

Self-efficacy, understood here as one's belief in their own ability to succeed at something, is highly correlated with choice of study and career (Beyer 2014; Hur, Andrzejewski, and Marghitu 2017). Huang's (2013) meta-analysis of studies into self-efficacy showed that boys were more likely to possess greater self-efficacy in computer science. Self-efficacy is reinforcing, success helps increase it and failure can undermine it (Pajares and Schunk 2001; Schunk 1991). Stoet and Geary's (2018) international study of science, mathematics and reading attainment, hypothesizes that girls often use their relative performance in a subject to influence their educational and career choices. Even where girls perform better in science and mathematics than boys, they will on average choose the reading-related pathway if that is where their relative strength lies, i.e. if they perceive themselves to be better at reading than at science and mathematics. The majority of girls were shown to be better at reading than science and mathematics, for boys the relative strengths were in science and mathematics and not reading. This complements other research (Wang, Eccles, and Kenny 2013) that shows that people with high mathematical and verbal skills are more likely to pick non-STEM careers than those who have high mathematical but moderate verbal skills. Girls make up a larger percentage of the high mathematical and high verbal group and are thus less likely to follow a STEM career. Whilst it has been shown that girls outperform boys in computer science GCSE (Kemp, Berry, and Wong 2018), it is currently unclear how male and female performance in

[2]Asian does not include ethnically Chinese students in the National Pupil Database.

computer science and ICT compares to other subjects; this is explored in this paper.

1.4 Female attainment in computing

There have been several studies that have looked into the effect of gender on academic performance, but few have focused on computer science or programming. At university level, Wagner's (2016) study of English computer science undergraduate results from multiple institutions over the course of 12 years showed significant underachievement for women compared to men in obtaining first class degrees (the highest qualification level), a difference that was not present in any other subject area. However, she noticed no significant differences in computer science for higher grades in general. Initial analysis of GCSE CS shows girls more likely to command the highest grade (A*) in 2014 (Bramley, Rodeiro, and Vitello 2015) and high grades (A*-C) in 2015 and 2017 (Kemp, Wong, and Berry 2016; Kemp, Berry, and Wong 2018). At A level girls tend to outperform boys (Department for Education and Skills 2007), including in computer science in 2015 (Kemp, Wong, and Berry 2016), although in 2017 boys outperformed girls (Kemp, Berry, and Wong 2018). It should be noted that girls outperform boys in nearly all subject areas (Richardson, Abraham, and Bond 2012; Voyer and Voyer 2014; Bramley, Rodeiro, and Vitello 2015), and, whilst girls might outperform boys at mathematics or science, they typically show a stronger relative performance in literacy (Stoet and Geary 2018).

At degree level larger female CS cohorts were correlated with a decrease in average performance among women (Wagner 2016). Bramley et al. (2015) found that regardless of a subject being mainly studied by men, women tended to do better in exams. However, this research looked at final grades and didn't control for the ability of entrants, i.e. how did students do in a subject compared to their grades in other subjects. Additionally, the impact of single-sex providers on secondary level computer science performance has not been studied. We cover both these factors below.

Computer science is considered to be one of the harder subjects at GCSE (Royal Society 2017), with students typically getting lower scores than in most other disciplines (Office of Qualifications and Examinations Regulation 2016). The reasons for this remain unclear, although the relatively recent introduction of the subject at GCSE and the inclusion of computer science on the national curriculum may well be contributory factors. Future changes in exam policy might go some way to fixing this.

Baron-Cohen's (2009) *empathizing-systemizing* theory states that boys are, on average, better at systemizing, and girls, on average, are better at empathizing, a system being "anything which is governed by rules specifying input-operation-output relationships [...] such as [...] computer programming" (Baron-Cohen 2004, 97). The ability to systemize has been correlated with increased ability in hacking (Bolgan et al. 2016), and Baron-Cohen's theory (ibid.) suggests that, from a purely psychological perspective, the average male would be more suited to courses that have large components of programming, such as computer science. However, studies into programming outcomes show no specific gender differences. Wilson (2002) found no difference between male and female performance in programming tests and Lau and Yuen's (2009) study of 14-19 year old students found no differences in performance between genders when controlling for student ability. However, as noted above, girls tend to outperform boys in all subjects and male relative strength lies in STEM subjects (Stoet and Geary 2018), which would be consistent with Baron-Cohen's model. Additionally, Spelke (2005, 9) argues that the *empathizing-systemizing* theory is wrong and "men [do not] have [a] greater intrinsic aptitude for mathematics and science".

Personal factors that can shape success in programming include self-efficacy and ability in mathematics (Wiedenbeck, Labelle, and Kain 2004; Wilson and Shrock 2001; Byrne and Lyons 2001). For programming, it has been shown that females can feel more inadequate, frustrated and with a lower level of self-efficacy compared to males when solving the same problems. Increased self-efficacy corresponds positively with programming outcomes (Lishinski et al. 2016). Several studies have linked spatial abilities to increased performance in computing and programming (Fincher et al. 2006; Cooper et al. 2015; Ambrosio et al. 2014). Male students are, on average, better at spatial reasoning (Reilly, Neumann, and Andrews 2017), with increased exposure to testosterone being correlated with better performance in spatial reasoning tasks (Aleman et al. 2004).

GCSE CS has one of the largest gender imbalances of all subjects, with only ~20% of students in 2017 being female (Kemp, Berry, and Wong 2018). It might follow that the girls taking the subject have overcome significant barriers to entry, meaning those sitting GCSE CS are particularly suited to the subject. Wagner (2016) tests a similar hypothesis when looking at girls taking CS degrees, but as noted earlier, finds that females underperform at the highest degree level. At GCSE, girls are more likely to command the highest grades in computer science (Kemp, Berry, and Wong 2018). Bramley et al. (2015) show GCSE gender grade differences are generally smaller for science technology engineering and mathematics (STEM) subjects than they are for the arts and the humanities, including computer science in the STEM categorisation. They also show that girls are slightly more likely to outperform boys at ICT than they are at computer science. This matches Department for Education and Skills (2007) data that shows girls less likely to outperform boys at A level computer science than at ICT. However, Wagner, Bramley et al. and the Department for Education and Skills fail to control for the academic profile of the students sitting the exams, i.e. does the small number of girls taking computer science mean that they, as a group, are more academically able than the larger more representative male group? Does the data support theories around male relative strength lying in STEM and female strength lying elsewhere (Stoet and Geary 2018)? The relationship between gender, academic ability and performance in GCSE CS is explored below.

2 Research questions

The overall aim of this paper is to analyse the current and the potential impact of a shift in curriculum towards computer science on female participation and achievement. The underrepresentation of girls in school level computer science is well known (e.g. Joint Council for Qualifications 2016b, 2016a); this paper will investigate the female GCSE CS cohort for factors that appear to influence participation and attainment. In particular, we will look at prior attainment, socio-economic background, ethnicity and school gender characteristic. We will explore whether female performance in GCSE CS is significantly different from the male population and how this differs from other subjects. This study is important as any differences noted here may have an impact on a girls' self-efficacy in computer science, and therefore their choices of further study and career. Throughout the paper we will compare the factors related to attainment and participation in the new GCSE CS against the legacy GCSE ICT qualification, we will then be able to make claims about the impact on female computing students of the curriculum change and the removal of the ICT qualification; a lesson that can be shared with other jurisdictions looking to emulate the model implemented in England. In short:

1. How do socio-economic and ethnic groupings impact female participation in GCSE CS?
2. To what extent does gender have an impact on attainment in GCSE CS, when controlling for school gender characteristic and overall student performance?
3. Given what the data says about GCSE performance, what will be the impact of a curriculum shift away from ICT towards computer science?

3 Methodology

3.1 Design

The English government's Department for Education (DfE) records demographic data for all students attending school (both state run and private) between the ages of 3 and 18 (Department for Education 2015b), along with individual students' exam results. This system is known as the *national pupil database* (NPD). Demographic data stored about students includes: gender, age, home location, ethnicity, parental wealth and school attended. Exam data includes exam board (the organisation setting the papers), course taken, date taken and grade. Combining the demographic data with exam results and descriptive data on schools from Edubase (Department for Education 2016a), such as the gender characteristic of a school, we can look at factors that correlate with participation and performance.

This paper will use secondary data analysis of the NPD with descriptive analysis for students sitting GCSE exams in 2016. Whilst 2017 data does exist, the grading system for the GCSE changed for mathematics and English, meaning that a direct comparison between subjects using that dataset would become less accurate.

3.2 Participants

This research will look at GCSE results for the 2016 English student cohort. This cohort numbers 583,547 students, with 60,736 (male=48,348; female=12,388) students taking the GCSE in computer science and 67,359 (male=40,289; female=27,070) taking the GCSE in ICT.

Where numbers of students differ in the data below, this is because explanatory variables are missing, and students with missing variables have been excluded.

3.3 Data analysis

Students were classified as being either female or male (coded 0 and 1 in the regression models used). No other values are stored in the NPD.

Students are recorded as eligible for *free school meals* if they are in some form of care or their parents have a limited income. Students who have qualified for free school meals at any point within the previous 6 years are categorised as *pupil premium* (PP) and schools will receive extra funding to support these students (Department for Education 2016c). This categorisation can be used as a rough indicator of social deprivation and a way of categorising students as working class (Baars, Mulcahy, and Bernardes 2016). However, this measure isn't without its critics, with Hobbs and Vignoles (2010) noting that over half of the poorest students wouldn't be categorised as pupil premium.

An alternative and more finely grained poverty indicator is the income deprivation affecting children index (*IDACI*). Each student has an IDACI score attached to their student record. This continuous value in an indicator of the wealth of the area that a child lives in, with values close to 0 reflecting richer areas and values close to 1 reflecting poorer areas (Department for Communities and Local Government 2015).

The NPD records the ethnicity of students using the categories: Asian (ASIA), Black (BLAC), Chinese (CHIN), mixed (MIXD), White (WHIT), any other ethnic group (AOEG), undeclared and missing (UNCL). Each of these groupings can be further broken down, for example Asian can be broken down into Bangladeshi, Indian, Pakistani and Asian other. Note that Asian here means all students from an Asian heritage excluding those with Chinese ancestry, the Chinese grouping allows for no further breaking down of the category. White students make up the majority of students in English schools, but it has been argued that the results of working class ethnic groupings are significantly different from other groups as to warrant separate analysis, in particular work has been done recently looking at the academic success of white working class boys (Baars, Mulcahy, and Bernardes 2016). To define working class students we will be using the ethnic category and the pupil premium status of the student. Other ethnic differences such as the performance differences between Bangladeshi and Indian students, will not be explored in this paper.

English school children sit mathematics and English standardised assessment tasks (SATs) at the end of primary school. These exams are also known as key stage 2 (KS2) results. Most students are 11 years old when they sit these exams.

These results are stored in the NPD as a grade between 0 and 5, with 5 being the highest grade possible for this age group. SATs are used as predictors of future attainment, with schools held accountable for the progress made by students based on their entry SATs grades. Additionally KS2 results of a subject cohort are used to influence exam grade boundaries (Benton and Sutch 2014). The paper will use this variable to look at mathematics profiles of boys and girls sitting GCSE CS compared to other subjects (Table 2).

The GCSE is the most common way for students to be assessed at the end of secondary school in England. Each exam sat at GCSE was assigned a grade on the A* to U range, with A* being the highest grade. GCSE grades are recorded for every student result in the NPD. For the purposes of this paper we are converting grades to numbers, this allows us to look at partial grade data, where 0.25 would be the equivalent of a quarter of a grade[3].

Table 1: GCSE grades and our numeric equivalent

Grade	A*	A	B	C	D	E	F	G	U
Point equivalent	8	7	6	5	4	3	2	1	0

Specific comparisons between GCSE Mathematics and other GCSE subjects will be made (Table 2). GCSE Mathematics covers topics including: statistics and data analysis, graphs, algebra, number manipulation, geometry, and real world relevance of maths (e.g. Assessment and Qualifications Alliance 2014b).

Each student result has a Qualification Accreditation Number (QAN), linking it to a course offered by an exam board. In 2016 there were 4 different exam boards offering computer science GCSEs in England. Each exam board sets its own syllabus and exam papers, coordinated by a national organisation, the Office of Qualifications and Examinations Regulation (Ofqual). Results to individual exam questions broken down by gender were not available to us.

As described earlier, girls on average outperform boys at GCSE exams and student academic ability needs to be controlled for when looking for differences in attainment for GCSE CS. Whilst the SATs grades provide background information about the mathematics and English performance of students, this result is generally 5 years before the GCSE CS exam and the ability of students might have changed significantly since then. Lacking the means to administer our own tests to students, we will adapt Stoet and Geary's (2018) model of looking for differentials between subjects, in our case GCSE examination results. We can then control for academic ability by looking at the difference between the average grade in a given subject, in most cases GCSE CS, and the average grade in other subjects.

For example a student taking computer science and three other subjects where they get A (7), B (6) and C (5), would have an 'ability' of 6, the average. If they

[3] There were changes in 2017 to grade some subjects on a 9 point system, the grades used in this paper are not comparable with the new grading system. `http://gov.uk/government/publications/gcse-new-grading-scale-factsheets`

scored a C (5) grade in computer science, they will be doing worse in computer science by 1 grade (i.e. 6-5).

As well as offering mixed-gender provision, schools in England can be exclusively for male or female students. The school gender characteristic for every school is stored in the Edubase database (Department for Education 2016a) and student records from the NPD can be linked to this information using the school's Unique Reference Number (URN).

To further explore Wagner's (2016) observation that larger female cohorts were negatively correlated with attainment at degree level, we will be looking at the female GCSE CS cohort sizes of schools. We will do this by filtering all schools where girls sat computer science, providing both the raw number of girls in a computer science cohort, and when looking at mixed schools, the percentage of the cohort who are female. We can then compare results for computer science for girls in these schools against their other subjects.

Descriptive statistics are used to show the relationship between gender and GCSE CS, GCSE ICT, and other subjects, focusing on: the mathematical abilities of students (Table 2); the ethnicity and working class status of students (Tables 3 & 4; Figures 2 & 3); the gender characteristic of a student's school (Tables 7 & 10). Descriptive statistics include the number of entrants (n and other indicators), means (M) and standard deviations (*SD*).

Logistic regression using Wald chi-square (Field, Miles, and Field 2012) is used to analyse the link between gender, ethnicity, wealth and the uptake of computer science, given that the outcome variable is categorical (Tables 5 & 6). Statistical models of participation only look at the students potentially able to take a subject, i.e. those students in a school where there was an examination group. In 2016 ~68% of students were in schools that had GCSE CS examination groups (Kemp, Berry, and Wong 2018).

Multivariate analysis using general linear models (Field, Miles, and Field 2012) are used to look at the impact of gender on attainment when controlling for student academic ability. To control for student ability, attainment in computer science is compared against the average grade in all other GCSEs, as noted above. In particular the research studies the impact of: gender (Tables 8 & 9); the gender characteristic of a student's school and the size of the female cohort (Table 11, Figures 4 & 5).

Additionally Welch two sample t-tests (Field, Miles, and Field 2012) are used to explore differences between mathematical abilities of female and male GCSE CS cohorts (Section 4.2.1) and the achievement of male and female students for different exam boards (Table 12).

The significance of p-values are given throughout as * for p-values < 0.05, ** for p-values < 0.01, *** for p-values < 0.001 (high significance). The p-values are given by $Pr(>|z|)$ for Tables 4 & 5 and $Pr(>|t|)$ for Table 12.

Where appropriate, effect-sizes have been reported (mostly as R^2): 0.2 is an indicator for a small effect-size and 0.5 an indicator of a medium effect-size (Coe 2002). Cohen's d was used in Section 4.2.1 and Cox and Snell R^2 values were used as our measure of the effect size present in the logistic regression on Tables 5 & 6

(Field, Miles, and Field 2012).

Standardised scores are indicated by *z values* on Tables 5 & 6. Where *intercept* is present on Tables 5, 6 & 11, it describes the outcome value, given 0 for the predictor values.

4 Findings

4.1 Population characteristics

For the 2016 dataset there were 5,136 schools running a GCSE qualification, of which 4,449 (86.6%) were mixed, 291 (5.7%) were male only and 396 (7.7%) female only. For GCSE computer science there were 2,337 schools, of which 2,063 (88.3%) were mixed, 123 (5.3%) were male only and 151 (6.5%) female only. Thus 45.5% of secondary schools offered CS, 46.4% of mixed schools, 42.1% of boys schools and 38.1% of girls schools.

For the data provided, 3.4% of GCSE CS students did not have the pupil premium field present in their student record.

For the data provided, 3.4% of GCSE CS students did not have the ethnicity field present in their student record.

For the data provided, 7.8% of GCSE CS students did not have the KS2 mathematics results field present in their student record.

The vast majority of students sit more than one GCSE (98%), for GCSE CS 60,679 (99.9%) sat more than one GCSE, allowing for comparisons to be made between results in computer science and other subjects.

4.2 Participation

4.2.1 Mathematics profiles

Table 2 shows that the GCSE CS cohort had a significantly higher mathematics SATs average grade than the non-CS population for females and males (CS female M=4.38; non-CS female M=4.10; t(12538)=41.577 p=0.000 d=0.36; CS male M=4.46; non-CS male M=4.10; t(77864)=99.013 p=0.000 d=0.44; Females taking GCSE computer science performed significantly worse at their mathematics SATs exam than their male counterparts (female M=4.38; male M=4.46; t(16368)=-10.129 p=0.000 d=-0.11); this matches the pattern seen in the general population (female M=4.11; male M=4.16; t(509247)=-23.790 p=0.000 d=-0.07), although the differences here remain small.

GCSE Mathematics results for the CS cohort also showed a significant difference from the non-CS population (CS female M=5.84; non-CS female M=5.06; t(12935)=53.003 p=0.000 d=0.44; CS male M=5.82; Non-CS male M=4.84; t(79901)=122.817 p=0.000 d=0.54). Within the CS cohort there was no significant difference between male and female GCSE mathematics results (female M = 5.82; male M = 5.81; t(17109)=1.356 p=0.175 d=0.01), this contrasts to significantly stronger results for females in GCSE mathematics for the overall population (female M=5.09; male M=5.00; t(521440)=17.353 p=0.000 d=0.05), as well as for the GCSE ICT cohort (female M=5.14; male M=5.06; t(54545)=6.488 p=0.000 d=0.05).

Schools that offered GCSE computer science had a higher average GCSE mathematics result (M=5.90) than those that offered ICT (M=5.03).

Table 2: Mathematics entry profiles by subject

SubjectName	n	Females	KS2 M(SD)	GCSE M(SD)	Males	KS2 M(SD)	GCSE M(SD)
Physics	109261	54203	4.64(0.52)	6.42(1.13)	55058	4.70(0.50)	6.45(1.14)
Chemistry	108611	54034	4.64(0.52)	6.42(1.13)	54577	4.70(0.50)	6.45(1.14)
Biology	106167	52750	4.63(0.53)	6.40(1.16)	53417	4.70(0.50)	6.43(1.17)
German	39781	20888	4.45(0.62)	5.94(1.31)	18893	4.58(0.57)	6.13(1.31)
CS	52971	10580	4.39(0.69)	5.82(1.52)	42391	4.45(0.65)	5.81(1.45)
French	109149	64279	4.37(0.65)	5.78(1.38)	44870	4.50(0.61)	5.93(1.37)
Spanish	68968	39402	4.36(0.65)	5.75(1.36)	29566	4.50(0.62)	5.87(1.36)
Music	31715	17385	4.34(0.70)	5.68(1.58)	14330	4.38(0.71)	5.67(1.64)
Physical Ed	95947	32737	4.28(0.67)	5.43(1.44)	63210	4.28(0.70)	5.12(1.55)
English Lang	268848	141221	4.25(0.71)	5.39(1.61)	127627	4.32(0.72)	5.38(1.66)
History	204038	106508	4.24(0.70)	5.40(1.54)	97530	4.31(0.70)	5.38(1.57)
Geography	185989	87733	4.23(0.71)	5.39(1.59)	98256	4.30(0.71)	5.37(1.59)
Bus Studies	61750	25607	4.23(0.67)	5.36(1.43)	36143	4.35(0.66)	5.43(1.42)
English Lit	324155	166862	4.21(0.73)	5.30(1.64)	157293	4.29(0.73)	5.29(1.68)
Relig Studies	209127	113108	4.20(0.72)	5.30(1.61)	96019	4.28(0.73)	5.32(1.64)
Drama	53316	32875	4.16(0.73)	5.18(1.59)	20441	4.15(0.76)	4.99(1.67)
Maths	476559	235788	4.13(0.76)	5.07(1.77)	240771	4.19(0.78)	4.99(1.84)
ALL	476559	235788	4.13(0.76)	5.07(1.77)	240771	4.19(0.78)	4.99(1.84)
ICT	58332	23346	4.13(0.74)	5.13(1.62)	34986	4.18(0.74)	5.03(1.62)
Art & Design	63407	43739	4.10(0.77)	4.98(1.74)	19668	4.00(0.83)	4.56(1.89)

4.2.2 Gender, ethnicity and pupil premium

Girls and working class students (signified here by being pupil premium) were underrepresented in CS compared to ICT. However, when combining gender and pupil premium Table 3 shows that among the girls taking computer science, those from a working class background make up a higher percentage of their gender grouping than their male equivalent (24.9%, vs 21.0%). This matches data from previous years (Kemp, Wong, and Berry 2016) and for girls is a figure closer to the percentage of pupil-premium students in the overall population (26.8%). For ICT, working class girls and boys are almost equally represented in their respective gender groupings (26.5%, vs 26.4%).

Table 3: GCSE pupil premium representation by gender

Gender		CS students	% of students taking CS	ICT students	% of students taking ICT
F	non-PP	8849	75.1	19022	73.5
F	PP	2927	24.9	6849	26.5
M	non-PP	37050	79.0	28521	73.6

M	PP	9824	21.0	10209	26.4

As seen in Table 3, working class students are underrepresented in computer science cohorts. When combining pupil-premium with gender and ethnicity (Table 4), we can see that not all ethnic groups are equally underrepresented, with Chinese working class boys and girls being better represented than their middle class peers (boys 42.9% vs 41.4% and female 18.9% vs 15.7%), and better representation of Chinese working class girls in CS than ICT (18.9% vs 15.0%), the only example of a female group that had better representation in CS.

Table 4: GCSE CS uptake as percentage of school population by gender, ethnicity and pupil premium (PP)

		Computer Science		ICT	
Gender	Ethnicity	non-PP	PP	non-PP	PP
F	AOEG	152 (10.9%)	87 (7.9%)	177 (17.4%)	171 (20.2%)
F	ASIA	1385 (12.0%)	492 (9.4%)	2340 (26.2%)	1076 (24.8%)
F	BLAC	408 (8.8%)	299 (6.4%)	624 (19.0%)	710 (19.8%)
F	CHIN	98 (15.7%)	18 (18.9%)	83 (20.2%)	9 (15.0%)
F	MIXD	359 (7.1%)	156 (5.6%)	567 (17.0%)	323 (16.2%)
F	UNCL	84 (6.6%)	40 (7.7%)	142 (15.7%)	60 (16.5%)
F	WHIT	6363 (5.6%)	1835 (5.4%)	15089 (20.2%)	4500 (19.3%)
M	AOEG	417 (24.4%)	273 (21.2%)	307 (27.7%)	261 (28.0%)
M	ASIA	3657 (28.4%)	1379 (23.3%)	3086 (35.0%)	1751 (36.0%)
M	BLAC	935 (18.9%)	812 (16.1%)	823 (26.7%)	945 (26.7%)
M	CHIN	259 (41.4%)	51 (42.9%)	123 (30.8%)	33 (37.1%)
M	MIXD	1364 (24.9%)	550 (18.8%)	917 (27.1%)	501 (24.8%)
M	UNCL	311 (23.9%)	120 (20.7%)	222 (25.9%)	96 (24.9%)
M	WHIT	30107 (24.9%)	6639 (20.1%)	23043 (30.2%)	6622 (28.7%)

4.2.3 Gender, ethnicity and IDACI

Splitting the students taking CS by gender and applying a logistic regression model (Tables 5 & 6) to look at the impact of IDACI on the chances of someone taking computer science, we find that the poorer a female student is, the more likely she is to take computer science (b=0.832; $\chi^2(1)$=153.32, p=0.000), this is the reverse of relationship seen in the male population (b=-0.529; $\chi^2(1)$=180.57, p=0.000). Both models have very low R^2 values and whilst there is a significant difference, the effect size is very small and this model fails to explain most of the difference seen (Cox and Snell R^2: for female =0.001; male=0.001).

Table 5: Model: Females taking CS predicted by IDACI score

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.8621	0.0166	-172.07	0.0000
IDACIScore	0.8323	0.0664	12.54	0.0000

Table 6: Model: Males taking CS predicted by IDACI score

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.0620	0.0090	-118.10	0.0000
IDACIScore	-0.5285	0.0396	-13.35	0.0000

Figure 2 places the GCSE CS and ICT populations into IDACI score deciles, we see that 7.2% of the poorest females in schools offering CS are taking the exam, versus 5.0% of the richest females. Amongst the male population the trend is reversed with the richest males being more likely to take CS (24.8%) than the poorest (21.1%).

Figure 2: GCSE computer science and ICT, influence of IDACI on uptake by gender

When looking at the likelihood of someone taking GCSE CS and ICT by gender, ethnicity and IDACI quartile (Figure 3), we see that the trend (as seen in Figure 2) of poorer females being more likely to take CS than richer females does not apply to all ethnic groupings. For Asian, Black and Chinese females, the richest grouping was more likely to be sitting computing than the poorest grouping. Only Mixed ethnicity and White females show increased uptake amongst the poorest grouping, when compared to the richest grouping.

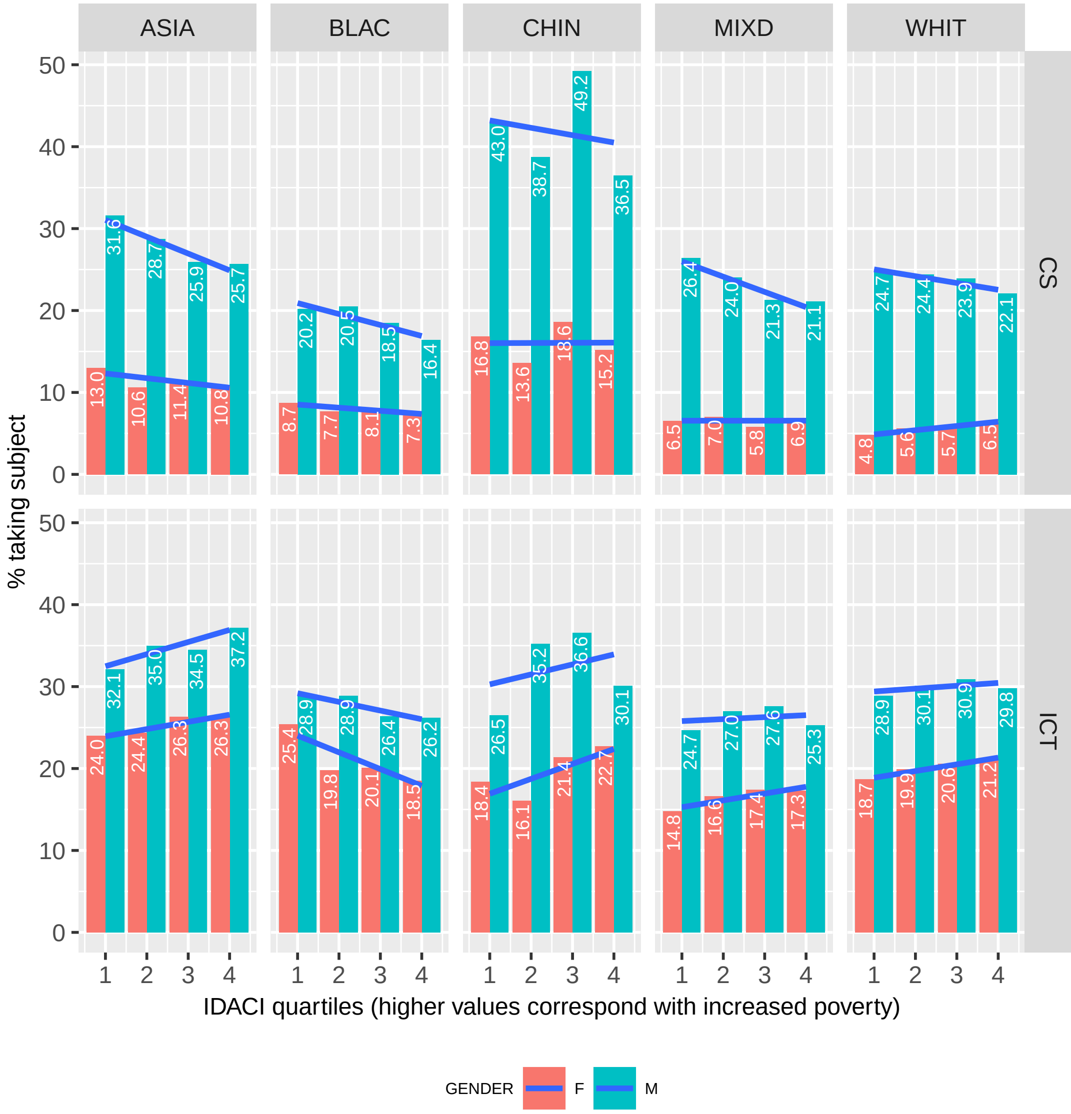

Figure 3: GCSE computer science and ICT uptake, gender, ethnicity and IDACI quartile.

4.2.4 School gender characteristic

Girls in single sex schools are more likely to sit a GCSE in computer science than those in a mixed school (6.8% vs 3.9%), however, a smaller percentage of all girl providers offer computer science compared to mixed providers (38.6% vs 40.4%).

Table 7: Percentage of females taking GCSE computer science and ICT by school gender characteristic.

School type	Total schools	Total females	CS schools	CS schools %	CS females	CS females %	ICT schools	ICT schools %	ICT females	ICT females %
Mixed	4134	246085	1670	40.4	9624	3.9	136	34.8	3706	9.1
Girls	391	40938	151	38.6	2764	6.8	1342	32.5	23331	9.5

4.3 Achievement

4.3.1 Relative achievement in computer science

As noted earlier, females outperform males at GCSE CS, however, when you control for 'ability' by using the average grade in other subjects, males significantly outperform females. A multiple linear regression was calculated to predict CS grades based on average grade in other subjects and student gender (Table 8). A significant regression equation was found (F(2,60673)= 47390, $p < 0.000$) with an R^2 of 0.61. A participant's CS grade increased 1.22 grades for each single grade increase of average grade, and males scored 0.31 of a grade more than females. Both average grade in other subjects and gender were significant predictors of CS grade. In contrast, the difference in ICT attributed to gender is statistically insignificant ($p > 0.05$). Male outperformance of females in computer science is only exceeded by results in mathematics (b=0.46; $p < 0.000$) and physics (b=0.41; $p < 0.000$).

Table 8: GCSE grade outcome predicted by average GCSE grade and gender

		Avg Grade (SD)		Estimate of subject result predictors		
Subject name	n	F	M	Avg.Grade	Gender	R^2
Maths	521790	5.09(1.78)	5.00(1.86)	0.99***	0.46***	0.68
Physics	127800	6.17(1.24)	6.16(1.25)	1.06***	0.41***	0.71
CS	60736	4.87(2.05)	4.70(2.02)	1.22***	0.31***	0.61
Science Additional	347749	4.81(1.49)	4.55(1.54)	0.97***	0.24***	0.72
Science Core	246700	4.38(1.48)	4.14(1.50)	0.89***	0.22***	0.72
Physical Ed	110951	5.35(1.51)	5.03(1.41)	0.76***	0.21***	0.52
Chemistry	127545	6.26(1.25)	6.05(1.27)	1.07***	0.18***	0.72
Bus Studies	70892	5.03(1.72)	4.81(1.76)	1.18***	0.16***	0.70
Biology	125890	6.28(1.23)	6.04(1.26)	1.03***	0.14***	0.74
History	237045	5.28(1.94)	4.83(2.02)	1.26***	0.05***	0.73
Music	40138	5.57(1.64)	5.32(1.76)	0.87***	0.05***	0.53
ICT	67359	5.21(1.77)	4.75(1.84)	1.00***	0.02.	0.59

Geography	222742	5.34(1.83)	4.89(1.82)	1.15***	0.02***	0.77
Drama	65948	5.53(1.46)	4.96(1.55)	0.73***	-0.19***	0.50
German	46152	5.54(1.39)	5.15(1.45)	0.90***	-0.21***	0.54
D&T Res Mat	45511	5.41(1.70)	4.53(1.74)	0.88***	-0.24***	0.61
French	129414	5.43(1.52)	4.98(1.57)	0.92***	-0.25***	0.54
Spanish	83120	5.52(1.63)	5.03(1.71)	0.92***	-0.25***	0.47
English Lang	306514	5.63(1.32)	5.06(1.41)	0.78***	-0.26***	0.69
English Lit	372197	5.65(1.40)	5.00(1.53)	0.83***	-0.32***	0.70
Relig Studies	246302	5.66(1.79)	4.91(1.97)	1.08***	-0.38***	0.69
Fine Art	48590	5.76(1.48)	4.98(1.65)	0.66***	-0.39***	0.48
Media/Film/Tv	42115	5.46(1.51)	4.59(1.61)	0.88***	-0.41***	0.60
Art & Design	77963	5.60(1.50)	4.64(1.61)	0.63***	-0.47***	0.48

Table 9 shows that both genders typically performed worse in CS than nearly all of their other subjects. Females only performed better in CS than in German, and males only performed better in CS than in German, French and Spanish.

There were 4,144 (Male=3,727; Female=417) who took both computer science and ICT GCSEs in 2016. Both groups typically performed worse in CS than in ICT (Male: M=-0.77 SD=1.4; Female: M=-0.93 SD=1.3).

A multiple linear regression was calculated to predict grades in other subjects based on CS grade and student gender. A significant regression equation was found for ICT (F(2,4141)= 2117, $p < 0.000$) with an R^2 of 0.51. A participant's ICT grade increased 0.60 grades for each single grade increase in CS, and males scored -0.20 of a grade less than females. Both CS grade and gender were significant predictors of ICT grade.

Focusing on English, there are significant regression equations for English Language (F(2,34242)= 11320, $p < 0.000$, R^2 of 0.40) and English Literature (F(2,42170)= 14950, $p < 0.000$, R^2 of 0.41). A participant's English Language grade increased 0.40 grades for each single grade increase in CS, and males scored -0.47 of a grade less than females. An English Literature grade increased 0.42 grades for each single grade increase in CS, and males scored -0.57 of a grade less than females. All predictors were significant.

Table 9: Average difference between GCSE computer science results and other subjects, by gender. Positive mean values signify students doing better in CS. Positive gender predictor values indicate males doing better

	Male		Female			predictors of subject grade		
Subject name	n	M(SD)	n	M(SD)	Diff	CS grade	Gender	R^2
German	5001	0.39(1.43)	1267	0.05(1.27)	0.34	0.49***	-0.47***	0.36
Music	2916	-0.17(1.65)	884	-0.30(1.50)	0.13	0.49***	-0.24***	0.35
French	9449	0.27(1.56)	3274	-0.30(1.43)	0.57	0.47***	-0.61***	0.33
Physics	16759	-0.65(1.19)	4187	-0.37(1.07)	-0.28	0.51***	0.10***	0.45
Biology	16299	-0.47(1.21)	4151	-0.43(1.07)	-0.03	0.49***	-0.14***	0.45
Chemistry	16756	-0.46(1.21)	4210	-0.43(1.07)	-0.03	0.51***	-0.13***	0.45
Spanish	6089	0.14(1.64)	2069	-0.50(1.50)	0.64	0.49***	-0.70***	0.32
Bus Studies	7440	-0.43(1.47)	1290	-0.54(1.38)	0.11	0.57***	-0.17***	0.45
Geography	18004	-0.41(1.43)	4299	-0.64(1.32)	0.23	0.56***	-0.34***	0.49
History	18456	-0.39(1.49)	4684	-0.65(1.38)	0.26	0.61***	-0.36***	0.47
Physical Ed	7002	-1.01(1.73)	1140	-0.72(1.61)	-0.29	0.36***	-0.06.	0.28
English Lang	26935	-0.39(1.52)	7310	-0.73(1.43)	0.34	0.40***	-0.47***	0.40
Drama	2682	-0.62(1.79)	1181	-0.86(1.66)	0.25	0.36***	-0.45***	0.28
D&T Prod Des	4290	-0.37(1.58)	543	-0.86(1.41)	0.48	0.52***	-0.70***	0.42
ICT	3727	-0.77(1.42)	417	-0.93(1.34)	0.16	0.60***	-0.20**	0.51
English Lit	33374	-0.49(1.55)	8799	-0.94(1.49)	0.45	0.42***	-0.57***	0.41
D&T Res Mat	4949	-0.77(1.64)	369	-0.99(1.52)	0.22	0.48***	-0.52***	0.41
Science Additional	27148	-0.98(1.44)	6963	-1.02(1.39)	0.04	0.48***	-0.08***	0.46
Maths	45002	-1.17(1.44)	11442	-1.02(1.37)	-0.15	0.51***	0.07***	0.49
Science Core	17117	-1.08(1.50)	4394	-1.09(1.47)	0.01	0.42***	-0.03.	0.41
Relig Studies	19867	-0.45(1.61)	5964	-1.10(1.52)	0.65	0.53***	-0.72***	0.41
Art & Design	2772	-0.74(1.93)	1870	-1.28(1.80)	0.53	0.32***	-0.85***	0.31
Fine Art	1819	-0.75(1.86)	1198	-1.30(1.79)	0.55	0.33***	-0.80***	0.32
D&T Food Tech	1159	-0.67(1.65)	603	-1.30(1.58)	0.63	0.45***	-0.89***	0.48
English Lang Lit	1914	-0.83(1.58)	361	-1.43(1.47)	0.59	0.34***	-0.30***	0.30
Media/Film/Tv	3158	-0.87(1.74)	747	-1.44(1.49)	0.57	0.39***	-0.72***	0.32
CS	48348	0(0)	12388	0(0)	0			

4.3.2 School gender characteristic

Table 10 shows that girls in all-girls schools do better in GCSE CS than their female peers in mixed schools (Average grade 5.74 vs 4.61). For ICT the grade difference between girls schools and mixed schools is smaller than for CS (5.69 vs 5.13). The difference between the CS grade and the average grade in all other subjects is also smaller in girls schools than mixed schools (-0.61 vs -0.93), whilst there is hardly any difference between grades in ICT and grades in any other subjects when comparing girls and mixed schools (-0.04 vs 0.06).

Table 10: Subject performance by school gender charactistic and pupil gender.
Negative difference values signify students doing worse in given subject

	Avg grade in subject(SD)				Difference from avg grade(SD)			
Sch Gender	Boys	Mixed	Mixed	Girls	Boys	Mixed	Mixed	Girls
Subject	Male	Male	Female	Female	Male	Male	Female	Female
Biology	6.48(1.15)	5.99(1.26)	6.19(1.24)	6.69(1.10)	0.10(0.62)	0.07(0.66)	-0.05(0.63)	-0.04(0.59)
Chemistry	6.46(1.21)	5.99(1.27)	6.16(1.25)	6.68(1.12)	0.08(0.67)	0.06(0.69)	-0.10(0.66)	-0.04(0.63)
Physics	6.53(1.17)	6.11(1.25)	6.07(1.24)	6.60(1.14)	0.18(0.65)	0.20(0.69)	-0.21(0.66)	-0.14(0.62)
Science Core	4.47(1.46)	4.12(1.49)	4.35(1.47)	4.75(1.46)	0.05(0.81)	0.12(0.83)	-0.15(0.77)	-0.20(0.73)
Science Additional	4.86(1.49)	4.54(1.54)	4.75(1.48)	5.26(1.43)	-0.01(0.82)	0.08(0.84)	-0.18(0.77)	-0.17(0.74)
Maths	5.70(1.76)	4.99(1.82)	5.02(1.76)	5.73(1.65)	0.39(0.96)	0.39(1.05)	-0.08(1.00)	-0.03(0.91)
CS	5.53(1.97)	4.63(2.01)	4.61(2.05)	5.74(1.80)	-0.40(1.23)	-0.66(1.31)	-0.93(1.30)	-0.61(1.07)
ICT	5.30(1.73)	4.71(1.84)	5.13(1.76)	5.69(1.69)	0.14(1.16)	0.06(1.21)	0.06(1.13)	-0.04(1.05)
Bus Studies	5.41(1.53)	4.75(1.77)	4.98(1.72)	5.39(1.67)	-0.19(0.88)	-0.26(1.00)	-0.34(0.95)	-0.39(0.91)
Art & Design	5.50(1.57)	4.58(1.58)	5.55(1.48)	6.14(1.50)	0.30(1.32)	0.35(1.41)	0.58(1.23)	0.20(1.13)
Fine Art	5.86(1.61)	4.79(1.59)	5.67(1.47)	6.33(1.36)	0.27(1.24)	0.31(1.39)	0.52(1.21)	0.33(1.10)
Geography	5.74(1.72)	4.80(1.81)	5.19(1.83)	6.15(1.61)	-0.13(0.85)	-0.22(0.93)	-0.19(0.91)	-0.08(0.82)
History	5.77(1.83)	4.73(2.01)	5.14(1.95)	6.07(1.66)	-0.11(1.00)	-0.34(1.13)	-0.30(1.07)	-0.10(0.90)
Relig Studies	5.67(1.82)	4.81(1.96)	5.54(1.80)	6.21(1.65)	-0.00(1.03)	-0.14(1.14)	0.25(1.04)	0.43(0.94)
English Lang Lit	4.24(1.51)	3.61(1.42)	4.01(1.42)	4.45(1.41)	0.17(1.04)	0.18(1.04)	0.47(1.05)	0.11(1.06)
English Lang	5.66(1.36)	5.01(1.40)	5.56(1.31)	6.01(1.28)	-0.08(0.81)	0.00(0.85)	0.20(0.82)	-0.02(0.79)
English Lit	5.73(1.46)	4.93(1.51)	5.56(1.40)	6.15(1.29)	0.07(0.84)	0.06(0.89)	0.33(0.83)	0.24(0.79)
Drama	5.53(1.53)	4.89(1.54)	5.42(1.47)	6.07(1.29)	-0.11(1.15)	0.10(1.20)	0.16(1.12)	0.03(1.01)
Media/Film/Tv	5.00(1.57)	4.57(1.61)	5.45(1.51)	5.58(1.46)	0.13(1.03)	0.15(1.09)	0.52(0.98)	0.33(0.91)
French	5.64(1.59)	4.90(1.54)	5.33(1.50)	5.95(1.56)	-0.49(1.07)	-0.68(1.13)	-0.46(1.02)	-0.30(1.02)
German	5.94(1.36)	5.04(1.43)	5.43(1.38)	6.10(1.33)	-0.49(0.97)	-0.71(1.02)	-0.51(0.94)	-0.44(0.87)
Spanish	5.74(1.65)	4.93(1.69)	5.40(1.62)	6.03(1.58)	-0.34(1.22)	-0.57(1.32)	-0.33(1.18)	-0.23(1.10)
Music	6.09(1.59)	5.21(1.76)	5.43(1.65)	6.25(1.42)	-0.15(1.04)	-0.10(1.26)	-0.22(1.15)	-0.15(0.96)
Physical Ed	5.47(1.45)	5.00(1.40)	5.28(1.50)	5.88(1.50)	0.17(1.02)	0.28(1.07)	-0.10(1.05)	-0.12(1.01)
D&T Food Tech	4.49(1.73)	4.15(1.63)	5.18(1.63)	6.07(1.50)	-0.30(1.00)	-0.03(1.11)	0.44(0.97)	0.33(0.88)
D&T Res Mat	5.19(1.83)	4.46(1.71)	5.27(1.69)	6.34(1.46)	-0.07(1.09)	0.04(1.13)	0.23(1.04)	-0.09(0.77)
D&T Prod Des	5.33(1.73)	4.34(1.74)	5.24(1.69)	5.83(1.60)	-0.19(1.10)	-0.21(1.15)	0.17(1.03)	0.06(0.90)

Breaking the computer science cohort into males and females attending mixed and single gender schools, we looked (Table 11) at the impact of student performance in computer science against all their other subjects using two predictive models: gender group size for mixed and single gender school and; the gender % of CS cohort for mixed schools.

The larger the number of girls in a cohort, the worse the girls did compared to other subjects. The effect is largest for girls attending mixed schools where every 5 extra girls in a year group taking CS corresponds with a 8% drop of a grade in an average school; the estimate was not as large for girls attending girls' only providers, where an additional 5 students corresponded with a 3.25% drop of a grade in an average school (p = 0.040). In comparison boys see no significant effect of gender group size on their attainment.

When looking at the percentage of CS students in a school who were female or male, a 10% increase in representation of girls results in a 6.5% decrease of a grade in an average school (p=0.000). For boys the reverse is true, a 10% increase in representation corresponds with a 4.9% increase of grade (p=0.0002).

However, it should be noted that in all cases the effect size is very small (R^2 < 0.03) and that the model explains very little of the variance that we see, other factors should be considered here.

Table 11: Difference between CS grade and average of other subjects predicted by group size. Models by gender and school type.

Model Predictor	Factor	Estimate	Std.Error	t.value	Pr(>|t|)	R^2
Mixed Schools (Male)	(Intercept)	-0.5855	0.0339	-17.2955	0.0000	
Grade_difference ~ n	n	-0.0024	0.0013	-1.8359	0.0665	0.00
Mixed Schools (Female)	(Intercept)	-0.6385	0.0289	-22.0947	0.0000	
Grade_difference ~ n	n	-0.0157	0.0028	-5.6372	0.0000	0.02
Single Sex (Male)	(Intercept)	-0.3260	0.1435	-2.2721	0.0248	
Grade_difference ~ n	n	-0.0020	0.0042	-0.4752	0.6355	0.00
Single Sex - Female	(Intercept)	-0.3619	0.0804	-4.5023	0.0000	
Grade_difference ~ n	n	-0.0069	0.0032	-2.1821	0.0307	0.03
Mixed Schools (Male)	(Intercept)	-1.0572	0.1154	-9.1602	0.0000	
Grade_difference ~ %cohort	per	0.0049	0.0013	3.6754	0.0002	0.01
Mixed Schools (Female)	(Intercept)	-0.6047	0.0370	-16.3558	0.0000	
Grade_difference ~ %cohort	per	-0.0065	0.0015	-4.4399	0.0000	0.01

When looking at the models in Table 13 using a scatter plot of schools[4] and lines of best fit, we can see in Figures 4 & 5 that there is considerable variance between schools. This helps explain the low R^2 values seen in Table 11.

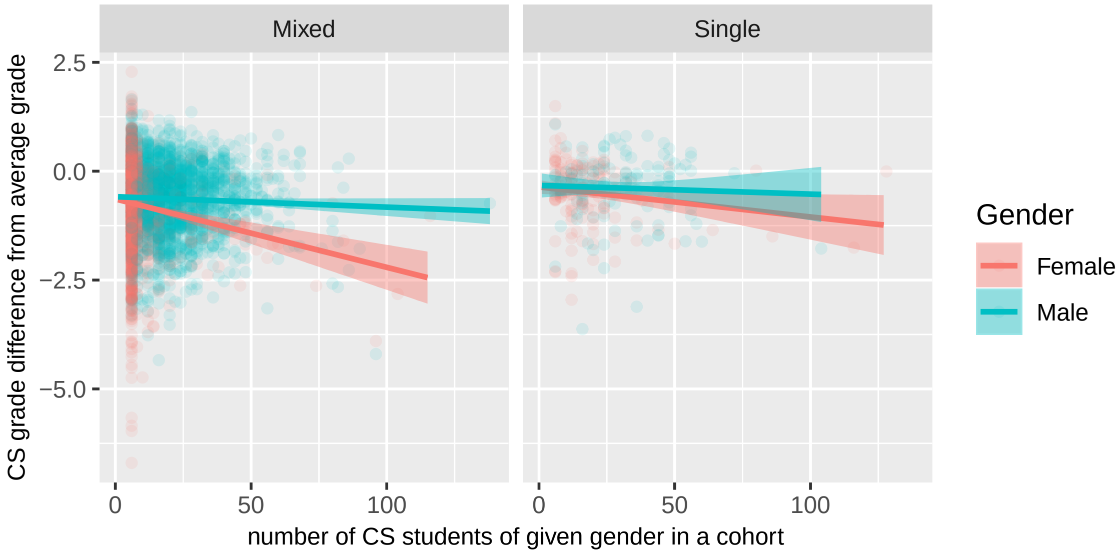

Figure 4: GCSE computer science cohort size (n) and relative performance by gender and school type

[4]To maintain anonymity of students all single-sex and mixed schools with cohorts fewer than 6 students have been rounded up to 6 students; all other schools are rounded to the nearest 2 and their grade differences randomly adjusted by 0.1 of a grade; mixed schools have had their percentages rounded to the nearest 2%. Lines of best fit are for the original dataset.

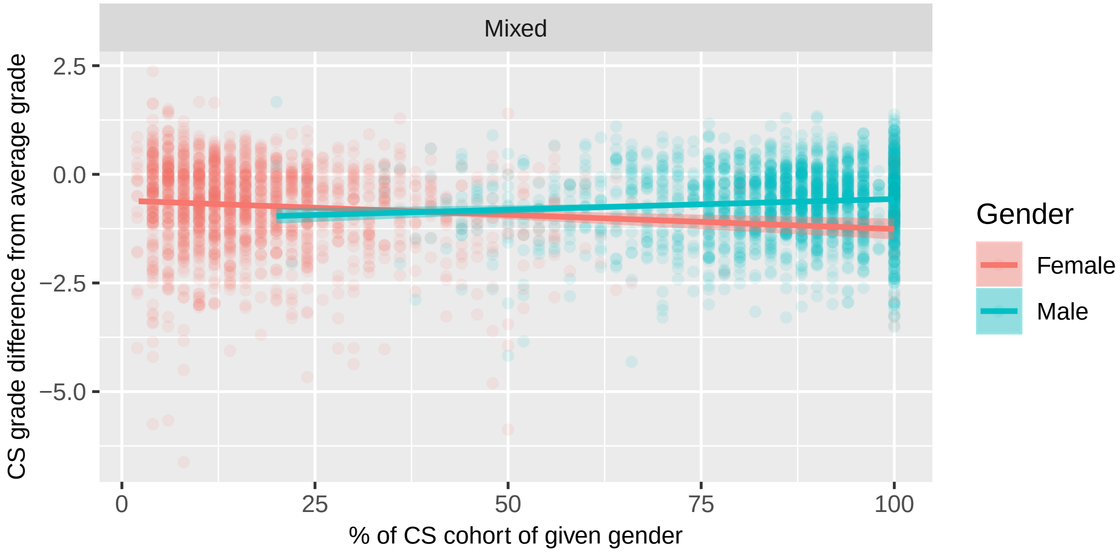

Figure 5: GCSE computer science cohort size (%) and relative performance by gender and school type

4.3.3 Exam board

Table 12 shows that all exam boards had significant differences between male and female performance in CS against their other subjects. Amongst the exam boards, female underperformance differs by up to a whole grade, depending on which exam was sat.

Table 12: GCSE CS results by exam board

Exam board	n F	n M	Overall average (SD) F	Overall average (SD) M	CS average (SD) F	CS average (SD) M	CS - overall F	CS - overall M	t-test Pr(>|t|)
50082917	9525	37385	5.72 (2.04)	5.34 (2.02)	4.92 (2.04)	4.72 (2.02)	-0.81	-0.62	0.000
6004908X	1810	7295	5.76 (1.97)	5.33 (1.94)	5.10 (1.97)	4.89 (1.94)	-0.66	-0.44	0.000
60064420	226	1123	5.59 (2.16)	5.36 (2.09)	4.30 (2.16)	4.47 (2.09)	-1.29	-0.89	0.000
60105446	814	2502	5.67 (2.11)	5.25 (2.08)	3.85 (2.11)	3.84 (2.08)	-1.81	-1.41	0.000

5 Assumptions

- Whilst we have not tested the normality of the data, the central limit theorem tells us that where n>30 we can assume normality for our datasets (Field, Miles, and Field 2012, pp43). In all t-tests used above n>30, allowing us to use the Welch t-test.
- We assume that the letter based grade system used for GCSE can be converted to a numerical scale and a linear relationship can be assumed, i.e. that the difference between an A* and an A is the same as the difference between a D and C, and a U and G.
- We assume that the ability of a student can be gauged from the average of their results in other subjects.
- Data used is only for 2016; 2017 and 2018 datasets are available but the grading system used is inconsistent across subjects.
- We assume that the results in CS and other subjects are comparable to each other and that individual exam boards have not inflated or deflated results.
- We assume that exams taken with different exam boards are equivalent and can be combined to form statistics about a GCSE CS population
- We assume that there are no major differences in teacher quality between different school types and schools serving female and male populations.
- In 2016 68% of students able to sit CS, throughout the report we focus on students attending these schools. 32% of students are missing from this analysis.
- The ethnic groups used are broad, and this paper has not looked into more fine grained groups such as Bangladeshi and Pakistani students.
- Where subjects are compared to CS, we take a group of the largest subjects (n>30,000), other smaller subjects might compare differently to CS.

6 Discussion

1. *How do socio-economic and ethnic groupings impact female participation in GCSE CS?*

In this report we do not treat gender as a homogenous group, but rather in conjunction with other factors such as ethnicity and parental wealth.

When categorised by pupil premium, of all girls taking computer science, female working class students show a higher relative representation than working class boys (24.9% vs 21.0%), but this falls short of being representative of the population (26.8%). Working class female representation in CS is still below that of working class female representation in ICT (26.5%) (Table 3). Other than Chinese girls, all ethnic groups show better representation in ICT than in GCSE CS, with white working class female students showing the poorest representation overall in CS (5.4%) (Table 4). We find that Chinese working class girls are the best represented group amongst GCSE female computer science students; this pattern of increased working class representation does not map to other ethnic minority groups (Table 4). However, we should note the small cohort size here (n = 116) when compared to other ethnic groups. In 2016 there were areas in England with close to 50% female representation in GCSE CS (Kemp 2017), many of them local authorities having a minority of white British students. Cultural factors might partially explain the better representation of ethnic minority girls, where 'professional' careers, including IT, are typically considered as a 'safe' choice for minority families, with perceived better or more stable financial returns (Archer, DeWitt, and Wong 2014; Wong 2016b).

In contrast to the findings that working class (defined by pupil-premium) students are less likely to take computer science than their richer (non-pupil-premium) peers, the more fine-grained poverty indicator IDACI, suggests that amongst girls taking computer science, poverty is positively correlated with uptake (Table 5; Figure 2). This is not the picture amongst boys, where the poorer are less likely to be studying CS (Table 6). Working class girls or their families might perceive CS as a subject with the potential to offer greater returns, with public discourse on the growing importance of technology in everyday life, including successful narratives of individual upward social mobility through digital entrepreneurship (e.g. British Computer Society 2018). Why this picture emerges for girls and not boys remains unclear. This might be an indication that the message about computer science being a subject for girls is being received less enthusiastically by middle class girls than their working class peers; with both groups being less receptive than the male population. Whilst the relative representation of working class girls compared to middle-class girls is better than that seen for boys, far more working class boys took computing than their female peers (n = 9,824 vs n = 2,927). Breaking down the gender IDACI model into separate ethnic groups (Figure 3) showed that increased uptake amongst the poorest students does not apply to Asian, Black and Chinese females. The trend of poorer females being more likely to take CS is heavily influenced by the large cohort of white female students, where the poorest are most likely to take the subject. While the white working class female population appears to be better represented than the white middle class female population, the percentage of white working class girls still trails other ethnic groups, as noted above. Additionally, using poverty indicators alone to predict the uptake of computer science explains little of the variance seen; there are clearly other factors at play and further research is merited here.

Whichever model we take for socio-economic status, pupil-premium or IDACI, computer science is less inclusive of girls and working class students overall, compared to ICT and the general population. The removal of the more representative ICT looks likely to have a significant impact on working class girls accessing a computing GCSE (Kemp, Berry, and Wong 2018).

2. *To what extent does gender have an impact on attainment in GCSE CS, when controlling for school gender characteristic and overall student performance?*

Girls do better than boys when taking GCSE CS (Kemp, Berry, and Wong 2018), however, girls significantly underperform in computer science compared to boys when controlling for their achievement in other subjects (Table 8). Female relative underperformance in computer science is less than that in mathematics and physics. This contrasts with findings around performance at university level, where females did worse at highest grades in CS than in mathematics and physics (Wagner 2016). GCSE ICT showed no significant difference between male and female results compared to their other subjects.

Relative underperformance might be explained by the different subjects boys and girls take. Some courses are considered easier to score high grades in than others, with STEM subjects being amongst the more difficult (Bramley, Rodeiro, and Vitello 2015; Office of Qualifications and Examinations Regulation 2015), and STEM subjects also being more popular amongst boys (Joint Council for Qualifications 2016b). This would bring an average male CS result closer to that of their other subjects, whilst an average female CS result would diverge from their other results. This might help explain some of the 0.31 of a grade difference. However, direct comparisons between CS grades and ICT and English grades show significant differences between genders; our model showed that gender explained 0.2 of grade in ICT, 0.47 of a grade in English Language and 0.57 of a grade in English Literature (Table 9). These differences when controlling for attainment in CS suggest that the 0.31 isn't entirely down to subject choice. More work on subject choice and CS is needed here.

All exam boards where girls sat GCSE CS showed significant ($p > 0.000$) differences between male and female relative performance in computer science against their other subjects (Table 12). Of note here are two exam boards where female underperformance is particularly high (-1.81) and particularly low (-0.66). Intraboard differences between boys and girls range between 0.19 and 0.40 of a grade. Work here is needed to look at individual assessment items to see if there are gender differences in performance, indicating some computer science qualifications are more suited to girls than others, and why.

All-girl schools have better CS uptake than mixed schools (Table 7), in line with Crombie et al.'s (2002) observation of better attitudes towards CS in all-female classes and counter to Quigley's (2017) finding about the ineffectual nature of introducing computer science to female only groups. It should be noted that the number of all-girl schools is low (n=151) when compared to mixed schools (n=1,670) and other factors that affect student choice within these schools are not present in this dataset.

Girls in all-girls schools do better in CS than their colleagues in mixed schools (Table 10), this might be explained by the high number of all-girls selective schools offering the subject compared to non-selective mixed schools (Kemp, Wong, and Berry 2016). Our model (Table 11) found that the larger the number of girls sitting computer science in a school the worse they do as a group against the average of their other subjects. This supports Wagner's (2016) findings at university level where grades went down with larger female cohorts. We find that the negative impact of large female groups on attainment is most acute in mixed schools and when females make up larger percentages of a mixed school CS cohort. For males in mixed schools, the larger the percentage of males, the better they do. In all cases our model of number or percentage of females in a cohort explained very little of the variance in attainment (see Table 11 and Figures 4 & 5), suggesting there are other more important factors that affect performance beside numbers of males and females in a class. Classroom dynamics, teacher gender and training, and school cultures around computer science need to be explored.

Overall reasons for female relative underperformance remain unclear, but likely involve a combination of subject choice, social (as discussed above) and psychological factors. Psychological factors around increased male self-efficacy (Huang 2013), spatial intelligence (Fincher et al. 2006) and systemizing (Baron-Cohen 2009) suggest that boys would outperform girls in GCSE CS; this clearly isn't the case when looking at raw grades (Table 10). But in a system where girls achieve more highly in general, these factors might help explain female relative underperformance in CS. The testing of these psychological hypotheses is beyond the scope of this paper, but they warrant further research into their impact on attainment in computer science. Compared to their other subjects, girls significantly underperform in CS, with similar underperformance in mathematics and physics; this supports research that female relative strengths, on average, fall outside STEM (Stoet and Geary 2018).

3. *Given what the data says about GCSE performance, what will be the impact of a curriculum shift away from ICT towards computer science?*

Computer science students show an increased mathematical ability (judged here by exam results) when compared to their peers (Table 2). Both male and female computer science students were significantly more able than their ICT equivalents, this suggests that some form of selection might be taking place to enter computer science courses, in line with previous findings and likely to negatively impact working class students (Kemp, Wong, and Berry 2016), or that more mathematically able students are choosing to pick CS. There was no significant difference between the mathematical achievements of female and male computer science students, where a difference was seen in the general population and amongst ICT students, albeit in both cases, a small one. ICT appears to roughly reflect the overall population in terms of mathematical achievement of students. Potential selection criteria based on mathematics, either school enforced or student chosen, supports the view that the introduction of computer science would create an elitist and selective subject (Rudd 2013).

Our research shows that the average female underperforms in computer science when compared to nearly all her other subjects; for boys, the difference is not as great, albeit still substantial (Table 9). Additionally the difference in performance between ICT and computer science grades is greater for girls than boys, suggesting girls who now take CS as a computing course, will feel that a computing course is harder than if they had taken ICT. Male and female CS results compared against English results see girls significantly outperforming boys at English, supporting findings for girls being stronger in verbal skills, and boys finding their strength in STEM subjects (Stoet and Geary 2018; Wang, Eccles, and Kenny 2013). It should be noted that girls do outperform boys at computer science (Kemp, Berry, and Wong 2018), but when controlling for attainment in their other subjects, boys outperform girls by 0.31 of a grade. These differences are important for female self-efficacy, where comparisons might be made to male students of similar abilities and/or their own results in other subjects. Building on Pajares and Schunk's (2001) finding that prior achievement links to subject choices and theories about subject choice in more gender equal countries such as England being heavily influenced by relative strengths (Stoet and Geary 2018), it follows that this relative female underperformance in GCSE CS will make it less likely for a female to pursue further study or a career in computing. This would not have been such a substantial issue for girls taking ICT, as female performance in ICT is in line with their other subjects. Additionally research shows girls more likely to take 'creative' computing courses that have more in common with ICT than CS (Wong and Kemp 2018). Girls are underrepresented in CS compared to ICT, and in 2017 there were 30,000 fewer girls sitting any computing qualification at age 16 than before the new curriculum was introduced (Kemp, Berry, and Wong 2018).

Socially, the CS 'environment' can be a 'chilly climate' for girls, with gendered discourses that undervalue the potentials of girls. Cheryan, Plaut, Davies and Steele (2009) argued that minor changes to computer classrooms can reduce gender stereotyping and gender expectations, especially the projection of identities available for girls in computing.

Amongst ethnic groups, black girls show the largest difference in uptake between ICT and computer science (Table 4). Poor representation amongst black students matches patterns seen in the USA (Google 2016) and contrasts with their more equitable representation in ICT. Clearly the shift away from ICT might help reinforce inequalities that are already present in access to specialist single science courses such as physics (Archer et al. 2017).

Whilst all-girl schools appear to be doing a better job than mixed schools in engaging girls to study computer science (Table 7), the numbers don't match the equitable offer seen in ICT providers. In 2017 when 2,350 mixed providers offered computer science, 382 had no female intake (Kemp, Berry, and Wong 2018). The factors that encourage girls to sit CS qualifications don't appear to be equally present in mixed providers, this might be explained by narrower perceptions of CS as a 'technical' domain typically reserved for boys (Wong and Kemp 2018), an opinion formed among students and teachers. More work is needed here.

The data in this report suggests that overall the move towards computer science and away from ICT is making computing a less equitable subject for females with a negative impact on their self-efficacy.

7 Conclusion

The computing qualification changes in England do not appear to be equitable for girls. The introduction of computer science at GCSE and the downgrading of the ICT qualification are creating a male dominated subject area, both in terms of participation and attainment when achievement in other subjects is taken into account. The removal of ICT and refusal to renew it has a strong potential to disenfranchise secondary school girls from computing, even when they choose to take computer science. Other jurisdictions looking to learn from the English curriculum model need to consider the range of qualifications they offer, the content of those qualifications and how they are assessed.

We urge the reader not to consider this paper as the last word on this, there is much that can be implemented to try and balance out the inequalities noted above. For example relative performance in a subject is not the only factor that impacts self-efficacy (Schunk 1991), minor changes to computing classrooms can reduce gender stereotypes and expectations, especially the projection of identities available for girls in computing (Cheryan et al. 2009), spatial skills can be targeted and improved (Parkinson and Cutts 2018), and there are other more equitable computing qualifications available beside the GCSE (Kemp, Berry, and Wong 2018).

The findings above should be read with some caution. The majority of girls still outperform boys in CS and the new computing curriculum in England has only been around since 2014 (Department for Education 2013a). The impact of prolonged study of the subject before selecting to take it between 14 and 16 needs to be explored, as do the reasons for female relative underachievement in computer science. Further analysis is needed here of learning pathways between qualification levels, more specifically how does relatively weak performance at 16 impact self-efficacy, subject choice for college and university, and choice of career?

Vitores and Gil-Juárez (2016) argue that we must look at the way we imagine computing, not just looking at ways to engage girls with our current conceptions. If the main computing qualification at age 16 in England is currently more attractive to one gender than another, and if one gender currently finds their strength in it and not the other, we should not wait for classroom pedagogy, society and individual characteristics to change, as to do so risks disenfranchising hundreds of thousands of girls from a *computing* education.

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